The Short and Medium-Term Effects of Climate Change on Vulnerable Households with Dispersed Family Networks

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Abstract

Weather has well-known impacts on agricultural yields, and climate change significantly increases the variability of productivity from year to year. Even as farmers adapt to changing conditions, this increase in variability is likely to be one of the constant impacts of climate change. Migration and marriage are often used to mitigate the risk, particularly in countries without the insurance and commodities exchanges that would stabilize rural economies. However, as climate change expands the risks, these same networks mean that the suffering of poor weather events is spread further than policymakers often recognize. We trace the impact of agricultural yields through networks by looking at child anthropometrics and household food insecurity in data from urban Kenya. We show that children and households suffer from events in distant parts of Kenya because they have kin who live there, highlighting interconnectedness in the context of climate change. We show that agricultural yields in rural areas affect household food insecurity in Nairobi up to five years later. However, weight for age and height for age show only contemporaneous effects; children are worse off if the crops do poorly in that year but are not affected by yields in the years before.

Introduction:

The impact of weather-driven changes in agricultural productivity on the lives of rural residents is a well-established fact. Poor rainfall affects stunting, wasting, and school enrollment, and adults, particularly women, suffer significant weight loss during such events (Hirvonen, Sohnesen, and Bundervoet 2020; Hirvonen 2016; Weinreb, Stecklov, and Arslan 2020; Paxson 1992). Importantly, agricultural productivity has effects on more than just farmers; everyone in an affected geographical area can suffer (or benefit) from agricultural productivity (Kaur 2019).

Families use marriage and migration to mitigate these risks (Giles and Yoo 2007; Abel et al. 2019; Deschenes and Greenstone 2007), but it can be difficult to trace the impact of shocks in one geographical area to households deliberately formed in different locations. If the dispersion of migration and exogamous marriage serve their purpose particularly well, we should be able to see the impact of climate-induced agricultural variability on connected households.

In this paper, which is awaiting a final round of data collection (November 2024) and one more season of corn yields (October 2024), we examine the preliminary evidence that poor households in Nairobi are heavily affected by events that occur where their kin live, often far from Nairobi. The JAMO (JAMAA na AFYA ya MTOTO) project is being conducted in two informal slum settlements in Kenya's capital city, Nairobi – Korogocho and Viwandani, and follows children who were younger than two at the beginning of the study in February of 2022. We measure welfare using the Household Food Insecurity Access Score (Coates, Swindale, and Bilinsky 2007) and the height for age and weight for age Z-scores (WHO Multicentre Growth Reference Study Group 2006) for the focal child. This unique study collected data on each child's kin (the mother's and father's side), including where they live.

We show that changes in agricultural yields in the counties where the child's kin live have long-lasting effects on household food insecurity. Agricultural yields in the current and preceding seasons affect food insecurity in the way we would expect. Increasing yields (compared to long-run averages) improve the household situation by decreasing food insecurity, and decreasing yields increase food insecurity. Somewhat surprisingly, yields have a long-run effect. Yields from agricultural seasons four and five years earlier have a large effect as well.

Yields also affect the child's anthropometric measurements, but only in the short term. Improved yields in the current season (meaning after this year's but before the next year's harvest) significantly increase the child's height and weight. Yields from before the current season have no effect on child health measures.

Importantly, rather than use rainfall to measure agricultural productivity, we use the Normalized Difference Vegetation Index (NDVI) data collected by satellite and validated against yield estimates produced by the Ministry of Agriculture in Kenya. NDVI is a reliable measure of potential yield even in situations where there are extreme weather events. For example, even though more rainfall is usually good for agriculture, rainfall at the wrong time and flood-level quantities are bad for agriculture. NDVI measures the photosynthate potential, and when used in the month before harvest, it can be considered a measure of potential harvest. As climate change continues to change the relationship

between weather events and agricultural productivity, measures like NDVI will become increasingly important.

The sample:

JAMO: The JAMO project, is conducted in two informal slum settlements in Kenya's capital city, Nairobi – Korogocho and Viwandani. These two areas have a combined population of about 90,000 (Wamukoya et al. 2020). They are characterized by inadequate sanitation, limited healthcare facilities, low-quality housing, high crime levels, unemployment, and poverty (Emina et al. 2011). Infant and child health indices are very poor (Kimani-Murage et al. 2014). While the two settlements share many commonalities, Viwandani has higher formal sector employment opportunities, more educated residents, and a more mobile population than Korogocho. Both settlements are multi-ethnic and include Kikuyu (30%), Kamba (24%), Luhya (18%), and Luo (12%) ethnic groups, among others, all patrilineal and patrilocal.

The JAMO study uses mixed methods to examine the relationships among kinship support, union formalization, and infant/child development outcomes longitudinally over six waves of survey data collection and three rounds of qualitative interviews. Wave 1 (conducted in March 2022) started with 1203 mothers aged 18-29 with a co-resident child aged 0-24 months. Data include socio-demographic characteristics of the mother and biological father, socio-economic status of the household (assets, food security), mother's fertility history and mental health, union status and history, and couple relationship quality. Data on children include vaccination history, nutritional status, illness episodes, and early child development. The kinship support module includes a roster of all reported close kin to the child (siblings, biological father, maternal/paternal grandparents, aunts, and uncles) with demographic attributes for each surviving kin, including age, location, employment status, and educational attainment. We also collected the type and frequency of support provided by and contact with the kin member for each wave.

Agricultural Yields: The Ministry of Agriculture produces estimated maize yields for the long season (harvest in October of each year) for each county in Kenya every year. The data are, unfortunately, spotty and not highly reliable. For example, the year 2022 is missing. Rather than relying on this data, we used the NDVI to measure yields, as follows. We measured the total NDVI for September, applied the Maize crop mask to the national map (isolating only the area where maize is known to be grown), and then took the average within each county. This method avoids mistaking forests for fields, and since it covers the full month of September, it can produce estimates despite cloud cover. We take the NDVI data from 2000 through 2023 and regress it on all available yield estimates, controlling for the county. The results produce an estimated maize yield for each county in each year from 2000 through 2023. [The data for 2024 will be available in a few weeks.] Rather than use the predicted yield for each county, we use the difference, in each year, from the long-run predicted yield.

Methods:

We produce eight NDVI measures for each household across five waves:

- NDVI anomaly lag -6 seasons (for example, in wave 1, in March of 2022, this would be based on the NDVI from September of 2015
- NDVI anomaly lag -5 seasons
- NDVI anomaly lag -4 seasons
- NDVI anomaly lag -3 seasons
- NDVI anomaly lag -2 seasons
- NDVI anomaly last season
- NDVI anomaly current season
- NDVI anomaly next season

These measures are then averaged across all reported kin, to develop an average NDVI for the household. Note that we include NDVI for the next season as a statistical check. It should not be possible for next year's yields to affect a household this year.

Using this average household exposure to agricultural yield variation, we examine four measures: 1) the Food Insecurity Score (0-27), whether the household is severely food insecure (0 or 1), the height for age Z-score and the weight for age Z-score.

Preliminary Results:

Table 1, below, shows that the average NDVI anomaly in the current season has the expected effect across all four measures. If your kin live in places that are doing well you have a lowered food insecurity score, are less likely to be severely insecure, and the focal child is both heavier and taller.

Note that the impact of the food insecurity score is much more long-lived: NDVI from up to five years earlier still has an important effect.

Discussion and Further Work:

These results are not driven (at least in whole) by the act of families shipping or not shipping maize from the rural areas to Nairobi. This is the impact of welfare in the rural areas (as measured by yields) being connected to welfare in the urban areas. We have data from the mother about what her kin do, whether she thinks they are wealthier than her, whether they help her and whether she thinks they would help her if she asked.

After adding the data that is forthcoming (one more round of household surveys and one more year of agricultural yields), we will investigate the mechanism that underlies this connected welfare. We will focus on how yields can have such a long-lasting impact on food security. We suspect that agricultural yields drive further migration and that this migration changes the composition of the households in Nairobi. An awful year for a mother's family in 2016 might cause her brother or sister to leave and move to join her household in Nairobi. Food insecurity is about much more than just the quantity of food available and we will draw on our data and previous qualitative research in Nairobi ((Madhavan, Beguy, and Clark 2018; Madhavan, Clark, and Schmidt 2020) to improve our understanding of this result.

Table 1 Agricultural Yields and Household Outcomes in Nairobi

	Food Insecurity Score	Severely Insecure indicator	height for age Z-score	weight for age Z-score
NDVI anomaly lag -6 seasons	-6.07	-0.297	1.496	0.281
	(0.278)	(0.398)	(0.192)	(0.812)
NDVI anomaly lag -5 seasons	**-28.637**	**-1.52**	0.84	0.199
	(0.000)	(0.000)	(0.278)	(0.773)
NDVI anomaly lag -4 seasons	**-40.466**	**-2.407**	1.535	0.996
	(0.000)	(0.000)	(0.138)	(0.276)
NDVI anomaly lag -3 seasons	**-24.966**	**-1.785**	0.398	-0.431
	(0.000)	(0.000)	(0.714)	(0.661)
NDVI anomaly lag -2 seasons	-4.067	-0.408	**-2.144**	-1.427
	(0.518)	(0.300)	(0.036)	(0.120)
NDVI anomaly last season	**-12.69**	**-0.979**	-0.088	-0.247
	(0.004)	(0.001)	(0.915)	(0.755)
NDVI anomaly current season	**-7.567**	**-0.648**	**1.854**	**1.756**
	(0.059)	(0.013)	(0.018)	(0.016)
NDVI anomaly next season	1.015	-0.372	1.372	-0.053
	(0.809)	(0.207)	(0.119)	(0.947)
wave 2	0.015	-0.016	-0.539	-0.181
	(0.985)	(0.786)	(0.001)	(0.242)
wave 3	-1.499	-0.074	-0.584	-0.252
	(0.114)	(0.271)	(0.001)	(0.164)
wave 4	1.106	0.042	-0.683	-0.433
	(0.206)	(0.477)	(0.000)	(0.011)
wave 5	0.265	-0.003	-0.67	-0.606
	(0.806)	(0.966)	(0.002)	(0.004)
number of kin	-0.078	-0.009	0.06	0.068
	(0.691)	(0.441)	(0.124)	(0.050)
number of kin^2 /100	0.681	0.059	-0.175	-0.182
	(0.245)	(0.082)	(0.128)	(0.083)
constant	13.528	0.693	-1.326	-0.71
	(0.000)	(0.000)	(0.000)	(0.027)
Number of observations	5343	5835	4805	4805

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